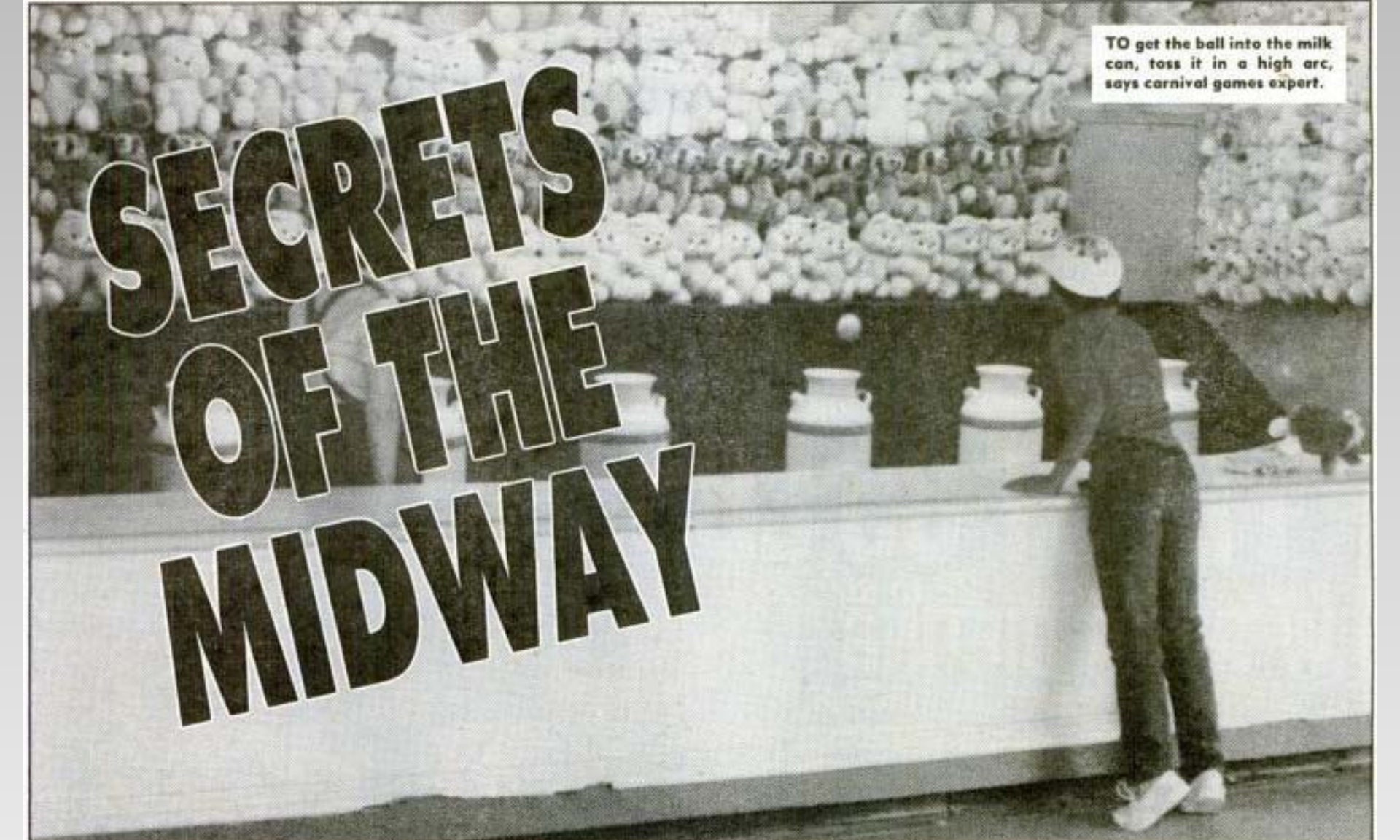


Background information as epistemic intervention

**Comments on Kotzen's "Selection Biases in
Likelihood Arguments"**

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SECRETS OF THE MIDWAY

TO get the ball into the milk can, toss it in a high arc, says carnival games expert.

Expert tells you how to win at carnival games

Conflicting measures

	P = police present		P = police absent	
	G = fair	G = rigged	G = fair	G = rigged
O = lose	1/8	1/8	1/8	1/8
O = win	1/8	1/4	1/8	0

LP:
$$\frac{P(\text{lose} \mid \text{fair})}{P(\text{lose} \mid \text{rigged})} = \frac{\frac{1}{2}}{\frac{1}{2}} = 1$$

LP*:
$$\frac{P(\text{lose} \mid \text{fair, present})}{P(\text{lose} \mid \text{rigged, present})} = \frac{\frac{1}{2}}{\frac{1}{3}} = \frac{3}{2}$$

LP:**
$$\frac{P(\text{lose, present} \mid \text{fair})}{P(\text{lose, present} \mid \text{rigged})} = \frac{\frac{1}{4}}{\frac{1}{4}} = 1$$

Epistemic interventions

Learning that a policeman was present:

(i) supports 'rigged' hypothesis:

$$\frac{P(\text{present} \mid \text{rigged})}{P(\text{present} \mid \text{fair})} = \frac{\frac{3}{4}}{\frac{1}{2}} = \frac{3}{2}$$

(ii) amounts to an *intervention*:

$$P(\text{present}) = 1$$

Epistemic interventions

Subsequently learning that I lost:

$$\begin{aligned} P(\text{lose} | \text{rigged}) &= P(\text{lose} | \text{rigged}, \text{present}) P(\text{present} | \text{rigged}) + \\ &\quad P(\text{lose} | \text{rigged}, \text{absent}) P(\text{absent} | \text{rigged}) \\ &= P(\text{lose} | \text{rigged}, \text{present}) (1) + P(\text{lose} | \text{rigged}, \text{absent}) (0) \\ &= P(\text{lose} | \text{rigged}, \text{present}) = 1/3 \end{aligned}$$

$$P(\text{lose} | \text{fair}) = P(\text{lose} | \text{fair}, \text{present}) = 1/2$$

Total support for 'rigged' hypothesis:

$$\frac{P(\text{lose} | \text{rigged}, \text{present}) P(\text{present} | \text{rigged})}{P(\text{lose} | \text{fair}, \text{present}) P(\text{present} | \text{fair})} = \frac{\frac{1}{3} \frac{3}{4}}{\frac{1}{2} \frac{1}{2}} = 1$$

Epistemic interventions

Epistemic support for H_1 over H_2 provided by learning E after learning the values of V_1 through V_n :

$$\frac{P(E | H_1)}{P(E | H_2)} = \frac{P(E | V_1, V_2, V_3, \dots, V_n, H_1)}{P(E | V_1, V_2, V_3, \dots, V_n, H_2)} \quad \text{LP}^*$$

Overall epistemic support for H_1 over H_2 :

$$\begin{aligned} & \frac{P(V_1 | H_1)P(V_2 | H_1) \cdots P(V_n | H_1)P(E | H_1)}{P(V_1 | H_2)P(V_2 | H_2) \cdots P(V_n | H_2)P(E | H_2)} = \\ & \frac{P(V_1 | H_1)P(V_2 | H_1, V_1) \cdots P(V_n | H_1, V_1, \dots, V_{n-1})P(E | H_1, V_1, \dots, V_n)}{P(V_1 | H_2)P(V_2 | H_2, V_1) \cdots P(V_n | H_2, V_1, \dots, V_{n-1})P(E | H_2, V_1, \dots, V_n)} = \\ & \frac{P(E, V_1, \dots, V_n | H_1)}{P(E, V_1, \dots, V_n | H_2)} \quad \text{LP}^{**} \end{aligned}$$

Upshot for the FTA

- Given $I =$ ‘carbon-based life observes the universe’, then $E =$ ‘the constants are fine-tuned’ provides no support for C over D
- The *total* support granted by learning I and E is in favor of D assuming $P(I|D) > P(I|C)$